Generative adversarial networks

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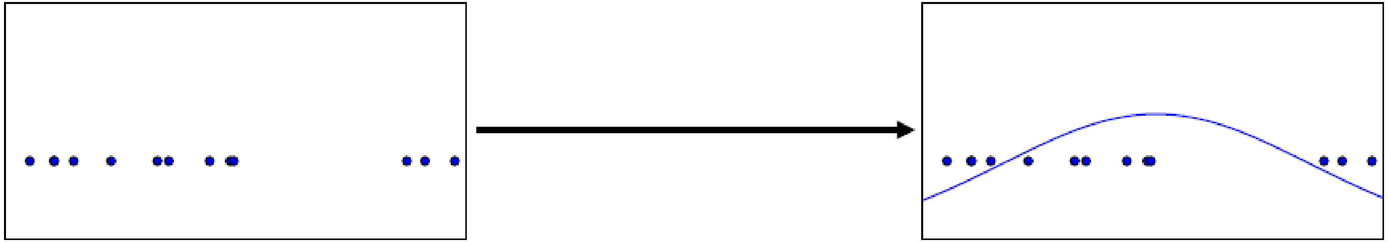
Machine Learning Practical - MLP Lecture 16
11 February 2019
http://www.inf.ed.ac.uk/teaching/courses/mlp/

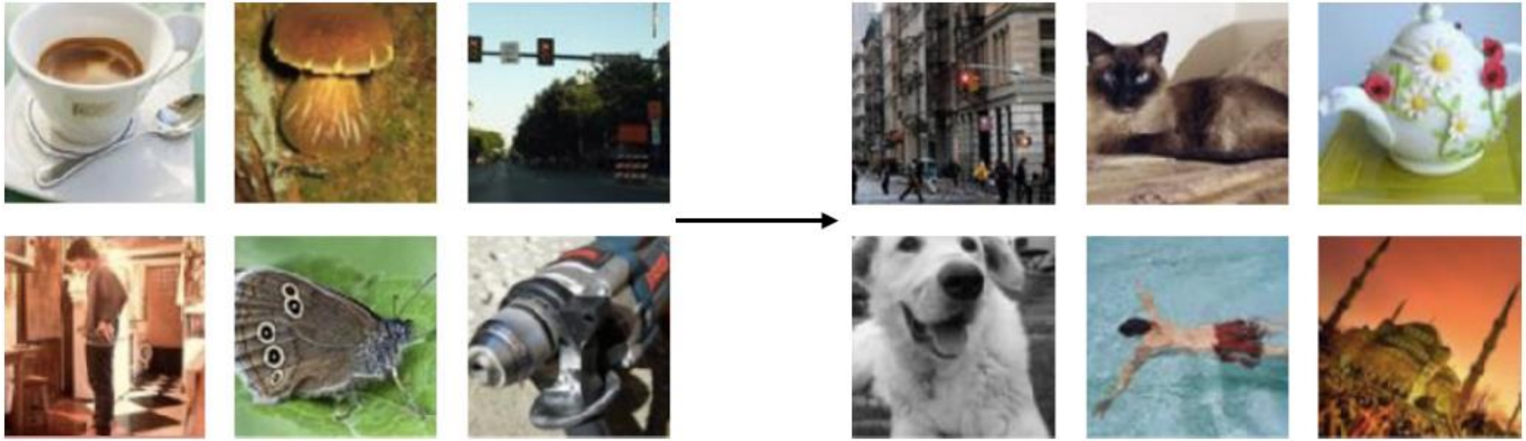
Slide credits: Ian Goodfellow

Generative modeling

- Density estimation



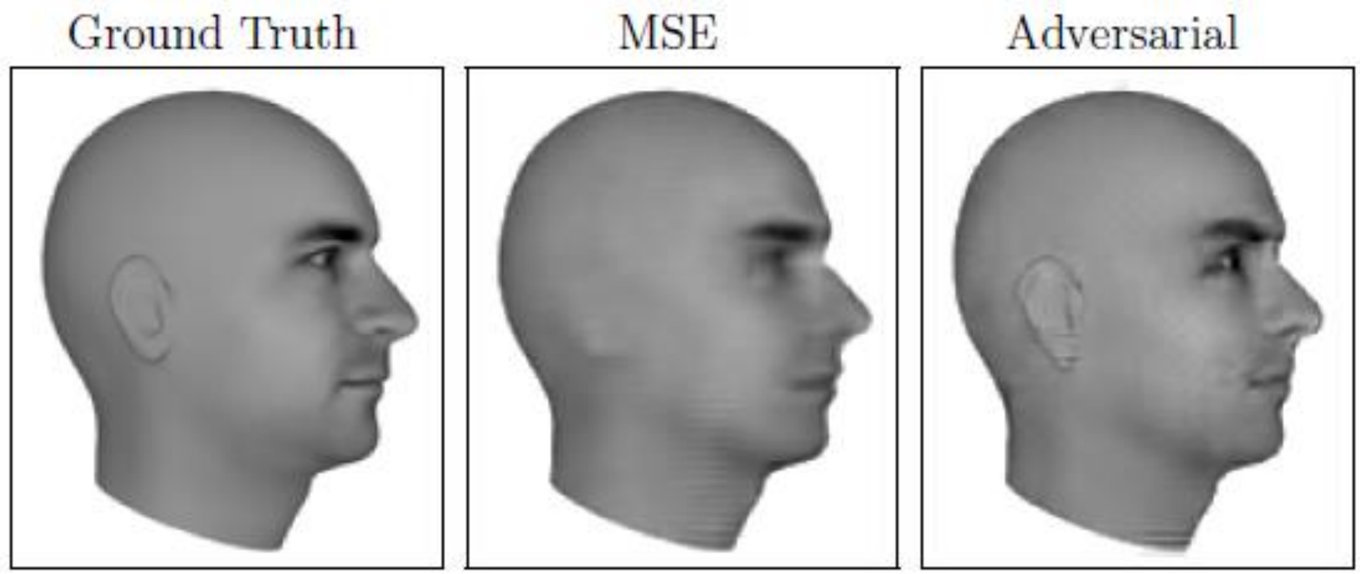
- Sample generation



Why are generative models useful?

- Test of our intellectual ability to use high dimensional probability distributions
- Learn from simulated data and transfer it to real world
- Complete missing data (including multi-modal)
- Realistic generation tasks (image and speech)

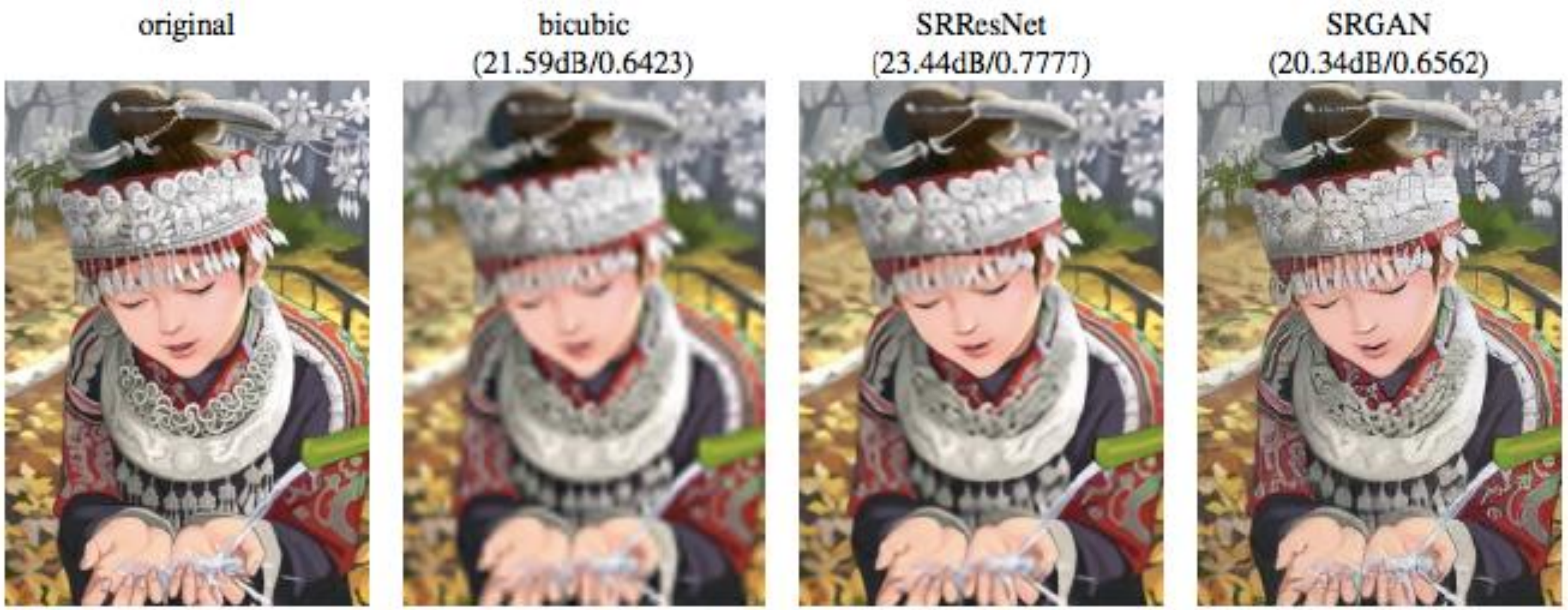
Next video frame prediction



Lotter et al 2016

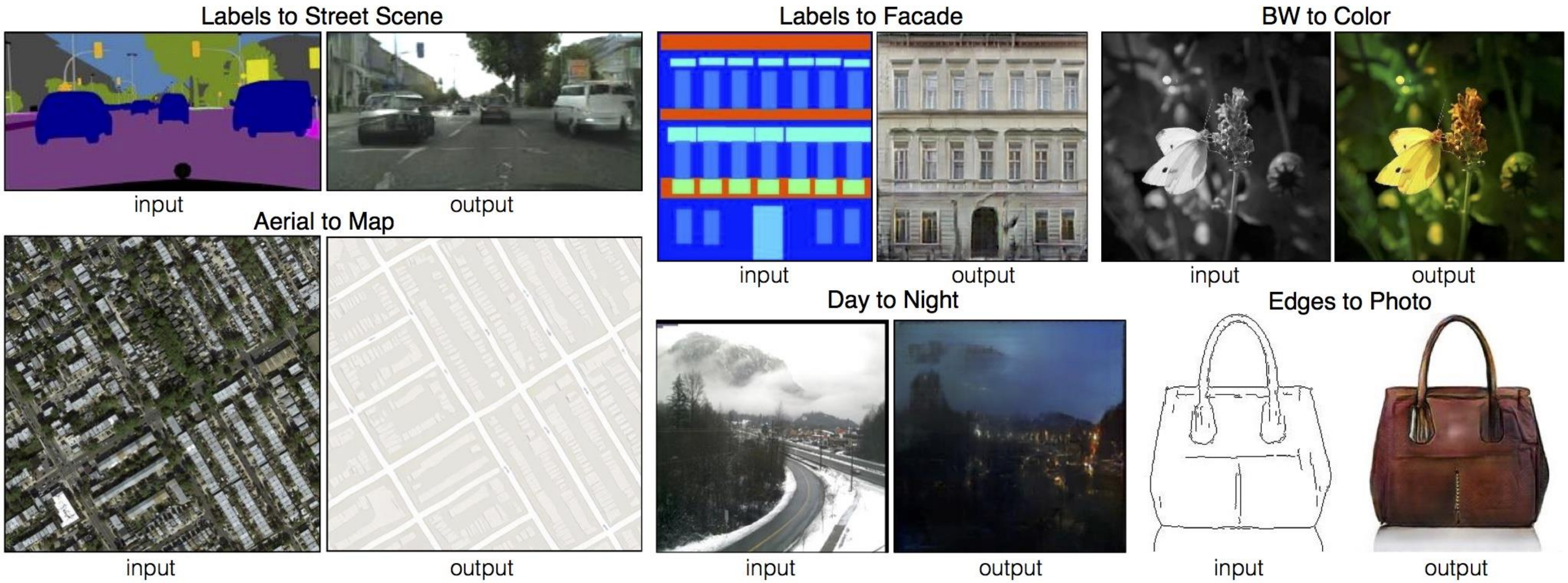
[Lotter et al. Deep Predictive Coding Networks for Video Prediction and Unsupervised Learning, ICLR'17]

Photo-realistic super-resolution



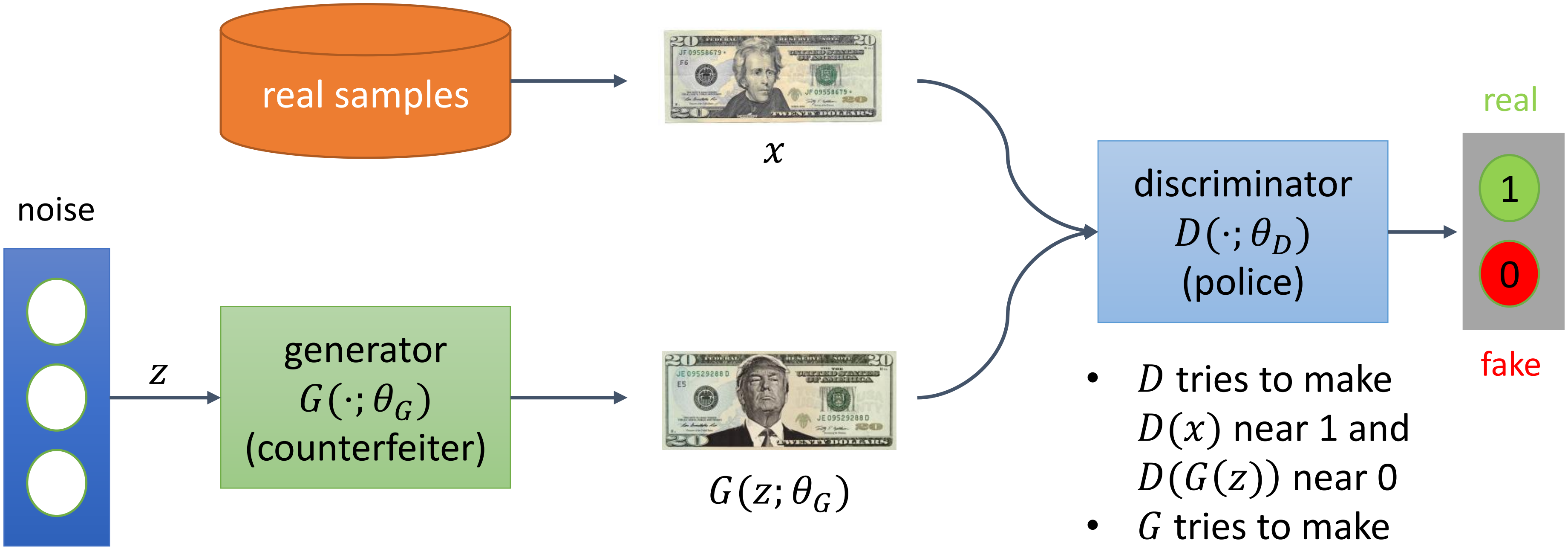
[Ledig et al. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network, CVPR'17]

Image-to-image translation



[Isola et al. Image-to-Image Translation with Conditional Adversarial Nets, CVPR'17]

Generative adversarial networks



- D tries to make $D(x)$ near 1 and $D(G(z))$ near 0
- G tries to make $D(G(z))$ near 1

Image credits: pinterest.com, snbchf.com

Minimax game

$$V(\theta_G, \theta_D) = \frac{1}{2}\mathbb{E}_{x\sim p_{data}} logD(x;\theta_D) + \frac{1}{2}\mathbb{E}_{z\sim p_z} \log\Big(1 - D\big(G(z;\theta_G)\big)\Big)$$

- $\min\limits_{\theta_G} \max\limits_{\theta_D} \mathrm{V}(\theta_G, \theta_D)$
- D wishes to maximise $\mathrm{V}(\theta_G, \theta_D)$ and controls θ_D
- G wishes to minimise $\mathrm{V}(\theta_G, \theta_D)$ and controls θ_G
- Solution to optimization at local minimum
- Game of two players with a solution at Nash equilibrium

Non-saturating game

$$J^D = -\frac{1}{2}\mathbb{E}_{x\sim p_{data}} logD(x;\theta_D) - \frac{1}{2}\mathbb{E}_{z\sim p_z}\log\Big(1 - D\big(G(z;\theta_G)\big)\Big)$$
$$J^G = \frac{1}{2}\mathbb{E}_{z\sim p_z}\log\Big(1 - D\big(G(z;\theta_G)\big)\Big)$$

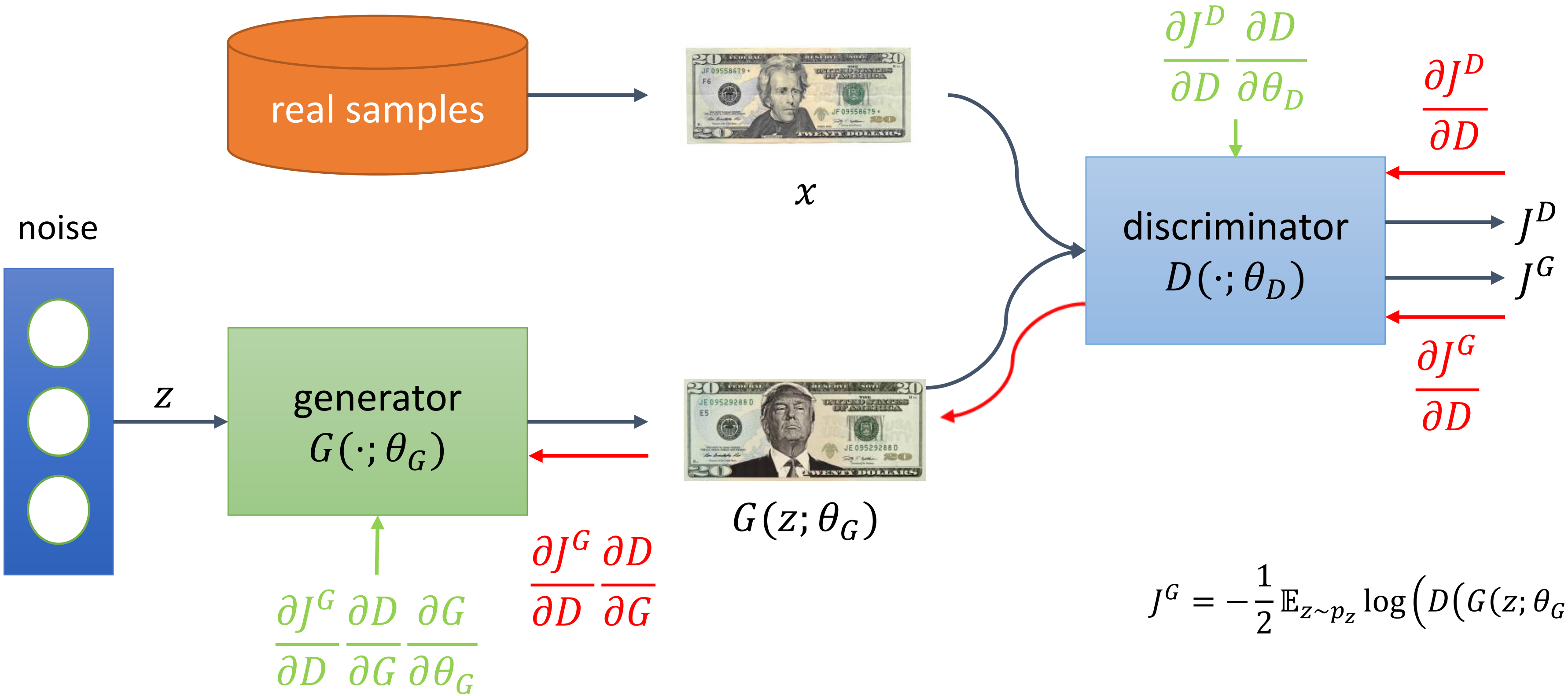
- Problem: when D successfully rejects generator samples, generator's gradient vanishes

- Solution:

$$J^G = -\frac{1}{2}\mathbb{E}_{z\sim p_z}\log\Big(D\big(G(z;\theta_G)\big)\Big)$$

Training GANs

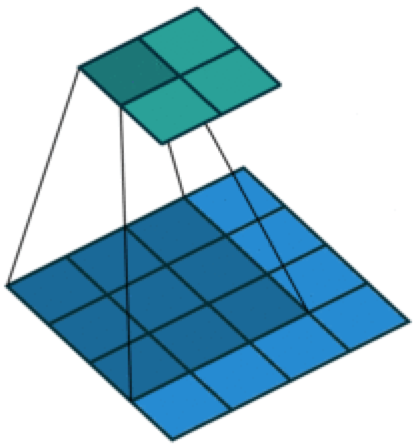
$$J^D = -\frac{1}{2}\mathbb{E}_{x\sim p_{data}} logD(x;\theta_D) - \frac{1}{2}\mathbb{E}_{z\sim p_z}\log\left(1 - D\left(G(z;\theta_G)\right)\right)$$



$$J^G = -\frac{1}{2}\mathbb{E}_{z\sim p_z}\log\left(D\left(G(z;\theta_G)\right)\right)$$

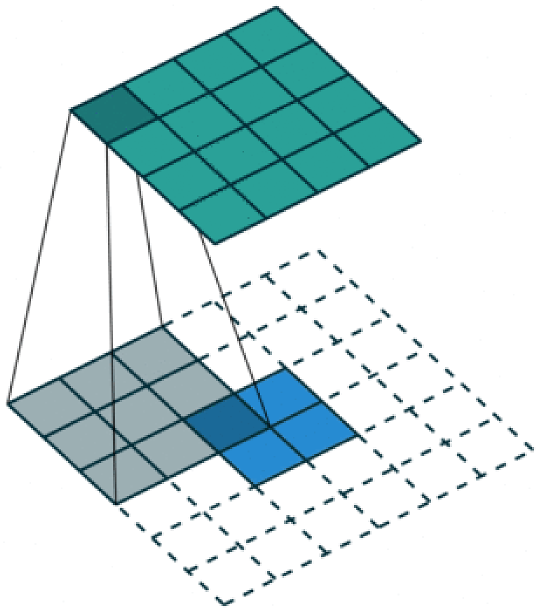
Review: Transposed convolution (deconv)

Convolution



Stride=1

Transpose convolution

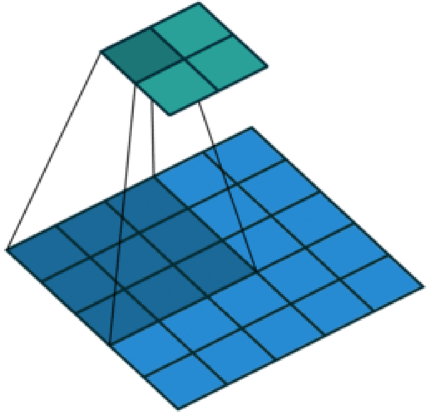


Stride=1

Dumoulin and Vision (2016), A guide to convolution arithmetic for deep learning, arXiv

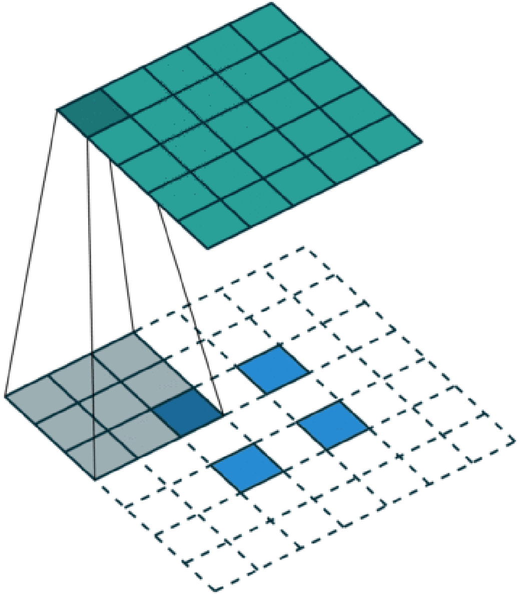
Review: Transposed convolution (deconv)

Convolution



Stride=2

Transpose convolution

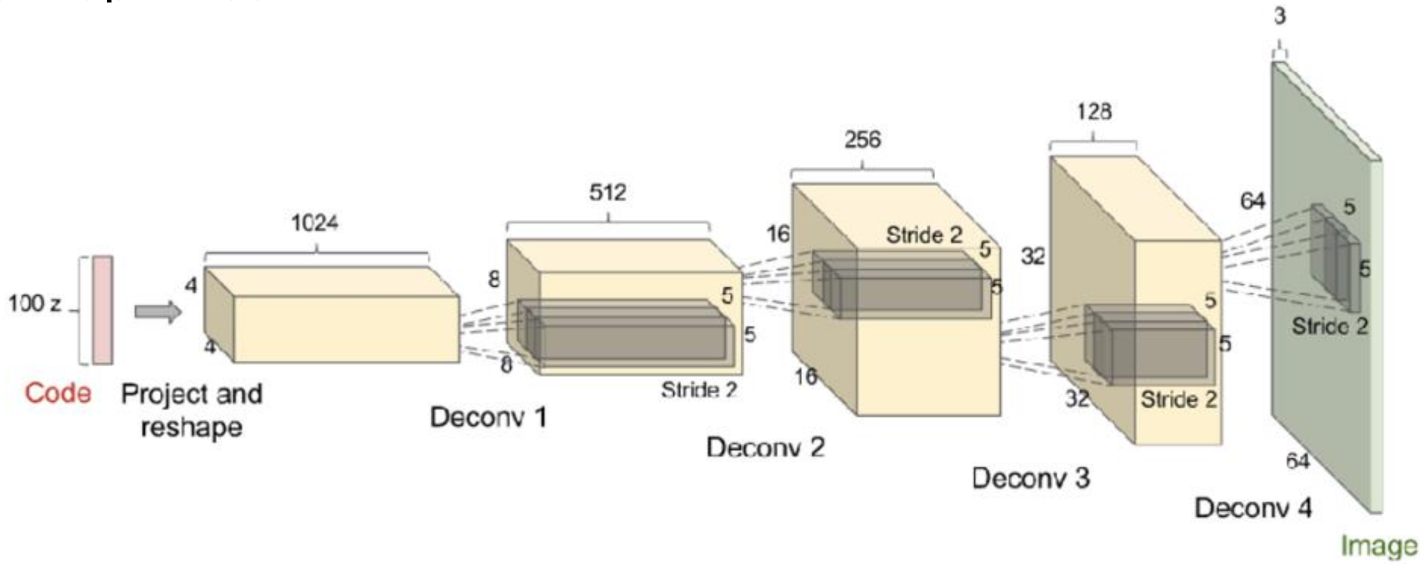


Stride=2

Dumoulin and Vision (2016), A guide to convolution arithmetic for deep learning, arXiv

DCGAN (generator) architecture

- Deconv weights are learned
- Deconvs are batch normalized
- No fully connected layer
- Adam optimiser



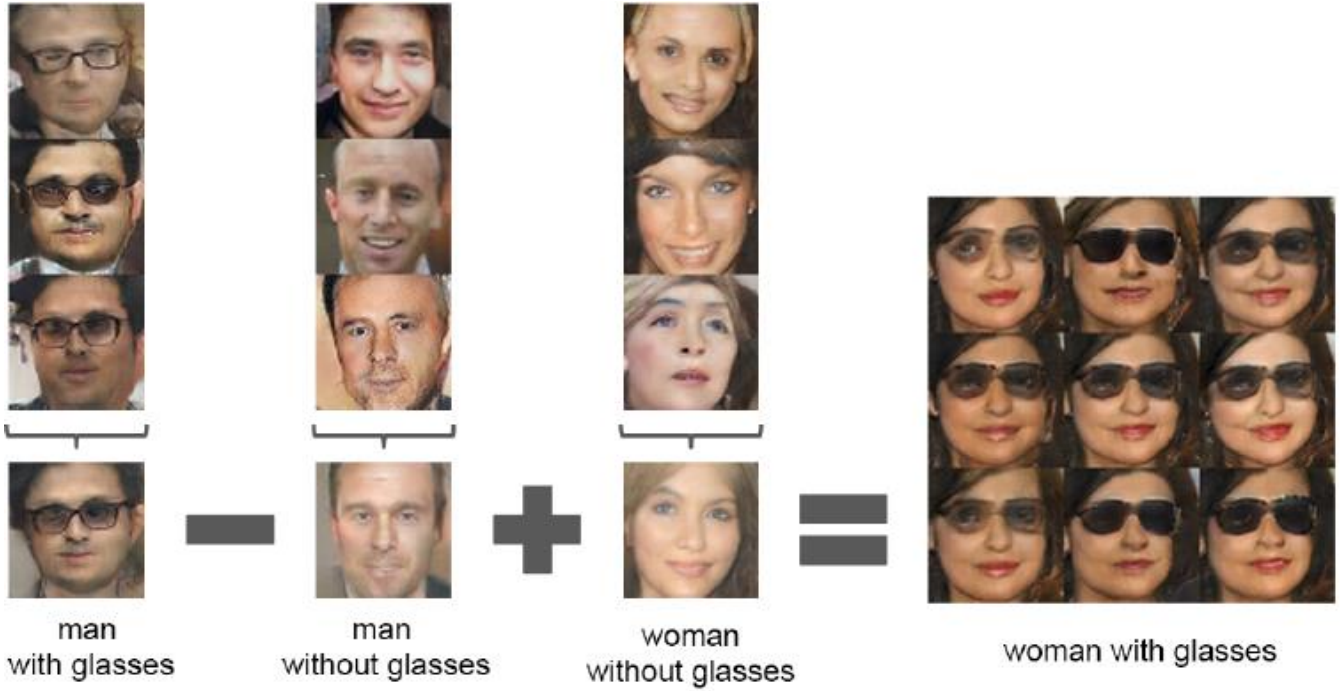
[Radford et al, (2015). Unsupervised representation learning with deep convolutional generative adversarial networks.]

DCGAN for LSUN bedrooms

High quality images on restricted domain

[Radford et al (2015). Unsupervised representation learning with deep convolutional generative adversarial networks.](#)

Vector arithmetic on face samples



Semantically meaningful latent space

[Radford et al (2015). Unsupervised representation learning with deep convolutional generative adversarial networks.]

Problems with counting and global structure

(Goodfellow 2016)

Salimans et al, S. (2016). Improved Techniques for Training GANs. NeurIPS.

Question

Is it a good solution for the generator to always produce only one real image?

Mode collapse

- Another failure mode is for the generator to collapse to a single mode
- If the generator learns to render only one realistic object, this can be enough to fool the discriminator

Salimans et al, S. (2016). Improved Techniques for Training GANs. NeurIPS.

Measuring GAN performance

Ask humans to distinguish between generated data and real data

- Subjective, requires training to spot flaws

Automating the evaluation (Inception score):

1. **Image quality**: images should contain meaningful objects (few dominant objects)
   - Feed images to Inception Net to obtain conditional label distribution $p(y|x)$
   - For each generated image, entropy over classes $\sum_y p(y|x) log\, p(y|x)$ should be low

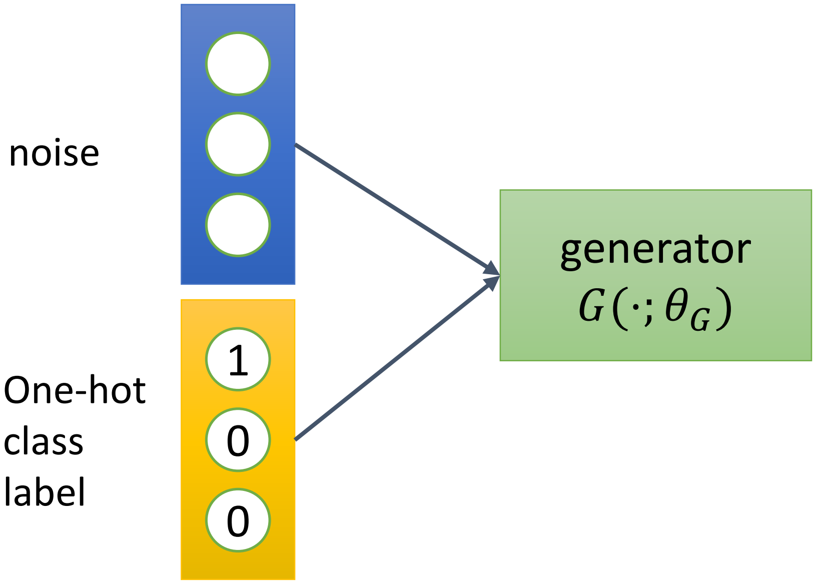
2. **Diversity**: the model should generate varied images (balanced over classes)
   - Entropy over generated images $\int p(y|x = G(z))dz$ should be high

- Combining two requirements ("how different is the score distribution for a generated image from the overall class balance?")

$$E_x KL(p(y|x)||p(y)) = \sum_{x \in X} p(y|x) \log \frac{p(y|x)}{p(y)}$$

Salimans et al, S. (2016). Improved Techniques for Training GANs. NeurIPS.

Class-conditional GANs



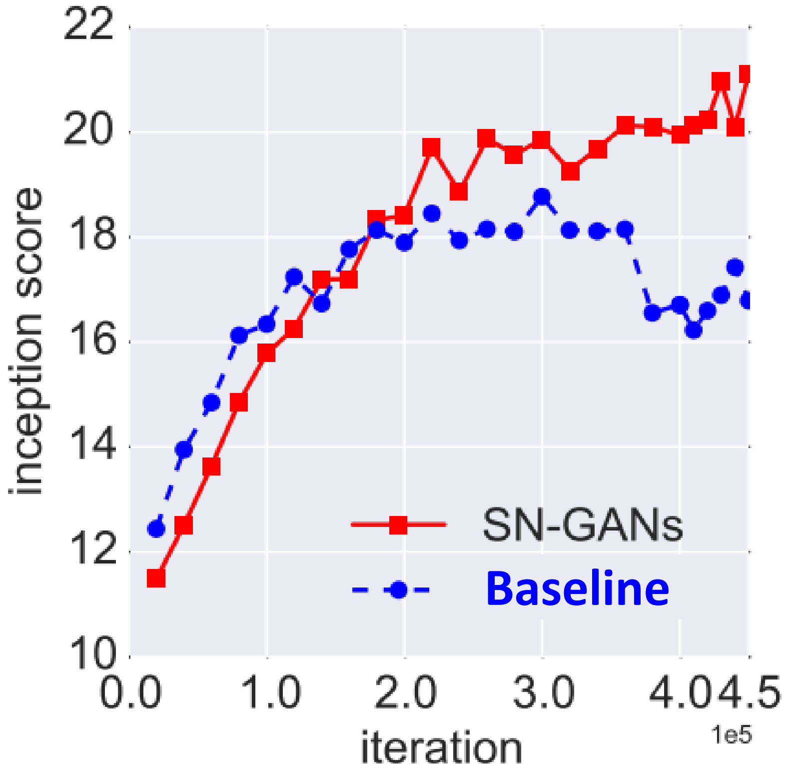
- Add class information in latent code z
- It is not unsupervised anymore

Mirza and Osindero (2014). Conditional Generative Adversarial Nets. arXiv.

Spectral normalization

- GAN training can be unstable
- **Culprit**: Gradient updates for G are unbounded
- **Observation:** First layer weights of G are ill-behaved when the training is unstable
- **Solution:** Apply spectral norm

- Spectral norm is the square root of the maximum eigenvalue of $W^T W$
  - $\sigma(W) = max \frac{|Wh|_2}{|h|_2} \rightarrow W/\sigma(W)$



Miyato et al. (2018). Spectral Normalization for GANs. ICLR.

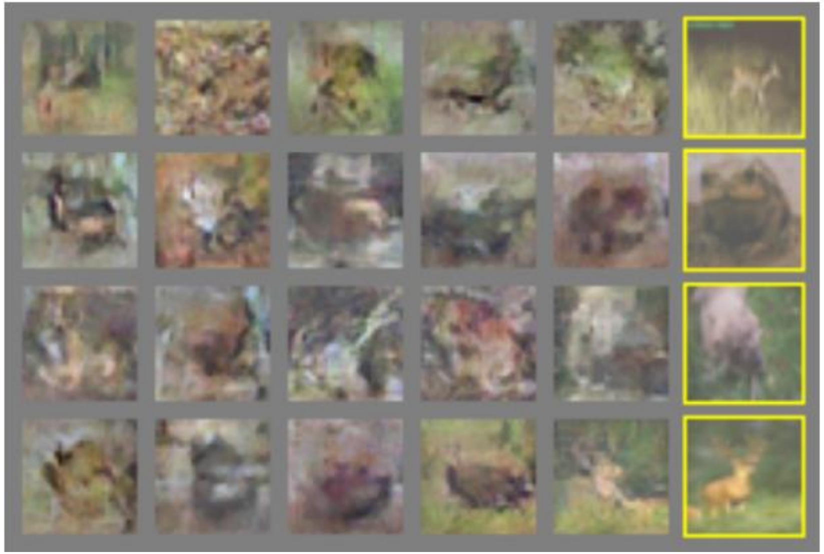
Scaling up GANs

BigGAN
- bigger mini-batch sizes (2048)
- more number of filter channels (~50% more)
- larger dataset (292 million images with 8.5k images, 512 TPU cores!)

improvements in
- state-of-the-art around 35% in Inception Score
- high-resolution images (512x512)

Brock et al. (2019). Large Scale GAN Training for High Fidelity Natural Image Synthesis. ICLR.

2014 to 2019



Goodfellow et al. (2014).

Figure 5: Samples generated by our model at 256×256 resolution. Sample sheets are available here.

Figure 6: Additional samples generated by our model at 512×512 resolution.

Brock et al. (2019).

Summary

- Generative models
- Training GANs
- DCGAN Architecture
- (Open) challenges
- Improvements

Reading material

Recommended

- Goodfellow et al, (2014). Generative adversarial nets. NeurIPS.
- Longer version Goodfellow, (2016). NIPS 2016 Tutorial: Generative Adversarial Networks.

Extra

- Radford et al, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks.
- Salimans et al, S. (2016). Improved Techniques for Training GANs. NeurIPS.
- Miyato et al. (2018). Spectral Normalization for GANs. ICLR.
- Brock et al. (2019). Large Scale GAN Training for High Fidelity Natural Image Synthesis. ICLR.

Coursework 2 overview

- Almost everyone did a very good job, code passed the unit tests, reports were well written and structured ☺
- Most people
  - successfully incorporated residual connections, BN to fix the “broken” network ☺,
  - further improved the results by adding L2 regularization and data augmentation ☺,
  - failed to analytically reason about the failed training and to show quantitative proof ☹.
- Some people failed to show the relation between the vanishing gradient problem and residual connection/BN ☹

Coursework 3

- Motivation and introduction to the project
- Research questions and project objectives
- Data set and task
- Methodology
- Baseline experiments (and any further experiments that have been done so far)
- Interim conclusions
- Plan for the remainder of the project, including discussion of risks, backup plans

Additional feedback for coursework

- Marking and moderating the coursework was **many** hours of work, both for Pavlos, Antreas and me, and a team of markers
- We strongly believe in treating everyone same
- Marking for report vs exam
- We will not be addressing issues that fall under Academic Judgement:
    - including discussion around whether a specific contribution is worth x amount of credit,
    - whether the marking was too strict/lenient,
    - comparing with colleagues, and similar issues,
    - very long descriptions (>2-3 sentences per objection point)
    - rude and sentimental emails
- We will be focussing first on obvious errors that you believe you have spotted